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USING DESIGN OF EXPERIMENTS TO DEFINE FACTORY SIMULATIONS FOR MANUFACTURING INVESTMENT DECISIONS

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ABSTRACT

For many manufacturing investment decisions production metrics only form part of the significant data, financial data such as cash-flow, Return on Investment, profitability are also critically important. However generating financial metrics from predicted or real production data is a non-trivial task. Moreover the nature of financial and production metrics are typically dissimilar in fidelity and interval and careful attention is required to standardise data for robust decision making. The paper demonstrates how a Design of Experiments approach can be used to systematically create simulation output combinations which can be used to understand and quantify the critical interactions between engineering and financial metrics. The results illustrate the need to carefully consider financial metrics, and the risk of reducing a systems performance within a period to a single financial value.

KEYWORDS: Discrete Event Simulation, Design of Experiments, P&Q

1. INTRODUCTION

A production system is traditionally considered as a combination of the materials supply, production planning, scheduling, control and material transformation functions. Many production control strategies have been proposed and used to manage production system operations. Such control strategies aim to regulate key metrics such as Work In Progress (WIP), cycle time or throughput, as well as their inter-relationships. Moreover simulation technology is available for developing and optimizing production control. Methods such as Discrete Event Simulation (DES) enable complex process chains to be examined to understand bottlenecks, excess inventory, overproduction, etc.. By representing a production system inside a simulation model it is possible to examine in virtual scenarios how a real system might work under predefined conditions. The influence of key characteristics, such as WIP or throughput can be readily examined during such virtual scenarios. A key weakness of the current state-of-the-art in this area is the lack of non-engineering metrics typically modelled. For decision makers the critical metrics are often not solely engineering but also financial. However automatically generating financial metrics from production simulation results is not a simple task requiring understanding of production and accounting practices. Moreover the nature of financial and production metrics are typically dissimilar in fidelity and interval.

In the production domain the tools available to engineering teams to provide financial assessment in support of operational decisions are typically based on costing methods. Typically such tools forecast product costs by utilising historical data to build relationships between production variables within the data and variable changes with the new or modified process. At the other end of the scale are the financial statements of the business. At this level metrics such as profit or loss are visible. There are two main statement types: a balance sheet presents a snapshot of the financial position of a business at a point in time, an income statement captures a business's financial performance over a period of time. For either the snapshot or accumulated metrics these are significantly removed from individual production activities and constrained in their form due to regulations on financial reporting.

As the production and financial variables of a manufacturing system are both high in number and dynamically interconnected in nature, modelling is required to predict future system behaviour. This paper investigates an integrated simulation methodology which incorporates both production and financial variables. The P&Q production problem and the DES software QUEST are used. The research focuses on how a Design of Experiments approach can be applied to systematically create simulation results which can be used to understand and quantify the critical interactions between engineering and financial metrics.

2. METHODOLOGY

Three approaches are brought together in this research (accounting practice, Discrete Event Simulation, and Design of Experiments). A focused introduction to each follows.

2.1 Accounting practice

Accounting is a highly regulated discipline responsible for the administration of business finances. Analysing company's accounts discloses how each performs and discloses market position in relation to the competition. Absorption costing assigns the costs accumulated during the production process to individual products [1]. These costs can be direct material costs, direct labour and indirect costs such as variable overheads and fixed overhead. The method calculates profit using Equation 1. COGS (Cost Of Goods Sold) includes materials used to create goods sold and used labour and overhead costs associated from production of goods. Labour under recovery is calculated by subtracting the used labour from the expected labour cost for the period, Equation 2. Similarly, overhead under recovery is calculated by subtracting the used overheads from the expected overhead cost for the period, Equation 3.

$$\text{Profit (or loss)} = \text{Sales} - \text{COGS} - \frac{\text{Labour under recovery}}{\text{recovery}} - \frac{\text{Overhead under recovery}}{\text{recovery}} \quad (1)$$

$$\frac{\text{Labour under recovery}}{\text{recovery}} = \text{Expected labour cost} - \text{Used labour cost} \quad (2)$$

$$\frac{\text{Overhead under recovery}}{\text{recovery}} = \text{Expected overhead cost} - \text{Used overhead cost} \quad (3)$$

2.2 Discrete Event Simulation

A system can be modelled as discrete or continuous. A discrete system is one in which the state variables change at set points in time. Discrete Event Simulation (DES) may be used effectively to simulate a manufacturing system [2], because its state may be represented as altering only at discrete points in time, e.g. when a workstation completes a process on a component. Johansson and Jackson [3] demonstrate the use of DES is a tool that can be used to generate customised information for decision support. In this case study a production facility for Printed Circuit Boards was modelled and the generation of customized information and real time forecasting demonstrated. Spedding [4] models a semi-automated Printed Circuit Board assembly line demonstrating the use of DES and ABC. Spedding concludes that the combination of cost modelling and simulation provide the potential for greater detail and the ability to account for the intrinsic variation of a dynamic manufacturing system. The major challenge associated with simulation is the significant engineering resource required to create an accurate model.

2.3 Design of Experiments

Factorial design considers all possible combinations of variables, leading to many experimental conditions. While this gives a thorough analysis, it requires significant computational effort. For a complex production system with a high number of financial and production variables a fractional factorial design can reduce the cost of investigation. An established method of achieving fractional factorial design is to use screening designs. Screening designs are small fractions of a full factorial design in which individual variable effects are considered dominant over joint variable effects. Orthogonal arrays define experiments of certain variable constituents and post-processing of the results (e.g. ANOVA calculations) enable the quantification of the influence of individual variable and variable interactions.

3. CASE STUDY

The P&Q problem, Figure 1, which was developed to demonstrate the theory of constraints by investigating a system with a bottleneck constraint, is examined herein. The system creates two outputs called P's and Q's. There are 3 raw materials and one purchased part which are used to make two products (P's and Q's). One unit each of materials 1 and 2 combined with one purchased part constitutes the chain for product P. One unit each of materials 2 and 3 constitutes the chain for product Q. There are four processes in the system A, B, C and D. Material 1 is processed by A, C and D, material 2 is processed by B, C and D and material 3 is processed by A, B and D. During process D product Q is made or the purchased part is added to create product P. A single operator is required to conduct each process. In the defined problem process B is a constraint. Output from the first two processes are stored in the Manufacturing Component Stores (MCS) until either process D is free, the other product specific component reaches the MCS or the purchased part store is replenished. The

product is then assembled and stored in the Final Goods Stores (FGS) before being shipped.

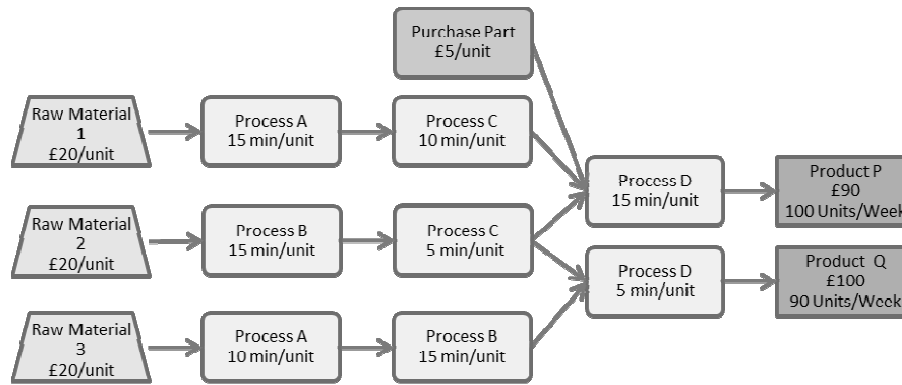


Figure 1. P&Q problem.

To govern the production system in the simulation a Material Requirements Planning (MRP) approach is employed. First a system demand was calculated from the number of weeks the model is set to run. The demand for product P and Q was set with a mean and a standard deviation. This sales demand schedule defines the variability within the problem. The sales demand was then used to generate the backward schedule for the MRP. The assembly works orders are forecasted backwards from the sales demand dates and the operational works orders, the starting operations of the system, are generated by backward forecasting from the assembly works orders. The system demand and works orders are shown in Figure 2. The problems internal constraint (i.e. process B) results in the market demanding more from the system than it can deliver.

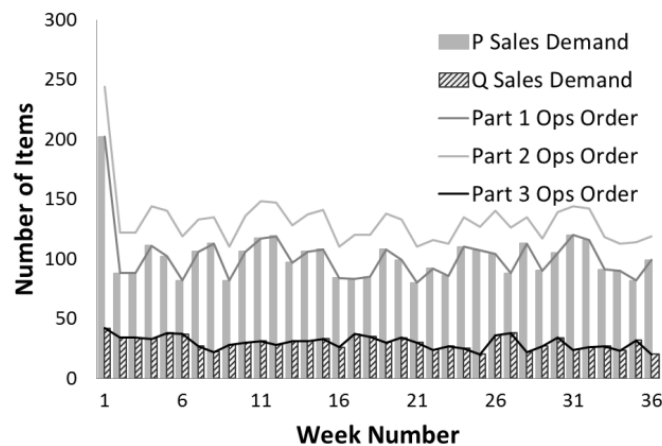


Figure 2. System demand and works orders.

The model is controlled using an excel interface. The interface enables the user to change the variables of the model. Simulations were run for both a 28 and 60 week period - to include an 8 week warm up period and then enable production to run in a converged state for 20 or 52 weeks. WIP, MCS and FGS values are

available from the simulations. WIP accumulates in processes A, B and C. MCS accumulates before the assembly process D. FGS accumulates once products are assembled, before shipping. The financial outputs include the calculated profit for the defined time period.

4. RESULTS

Initially a series of predictions were performed to understand how the pure financial input variables influenced Profit. An orthogonal array was used to construct a series of simulation runs considering 5% variation to the selling price of the P and Q products. ANOVA analysis was then undertaken on the simulation output to calculate the contribution to the predicted variation in Profit. P was found to contribute 90% and Q 10%, demonstrating the selling price of the P was the dominant factor. This result is explained by the fact that the average weekly demand for Ps is approximately 3 times that for Qs.

A similar study was then performed for raw material and purchased part costs, this time with 10% variation. The greatest percentage contribution was Material 2 at 59%, followed by 36% for Material 1 and 3% for Material 3, Figure 3a & 3b. This supports the finding of the previous study as Materials 1 and 2 form product P, and therefore have the greatest effect on profit when manipulated. The ANOVA results also determined that there was no significant interaction between the raw material and purchased part costs, Figure 3a.

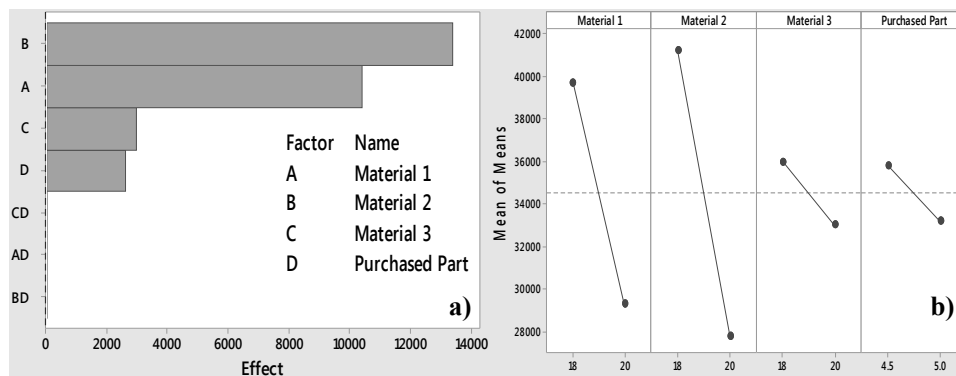


Figure 3. Pareto chart and main effects plots (response is Profit, $\alpha = 0.05$).

A third study considering all the previous input variables varying by 10% was then undertaken. In this case the greatest percentage contribution was the selling price of product P at 81%. It is much greater than the other factors as product Q contributed 8.2%, Material 2 contributing 6.6% and Material 1 contributing 4%. This illustrates, for equal percentage change, product selling price is more influential on Profit than material cost. This result is logical as the selling prices are greater in magnitude than the material costs. The Pareto chart (not presented) for this analysis also revealed the interactions between the examined inputs (material costs and selling prices) were negligible.

A similar screening study was then undertaken to consider production inputs, Figure 4a & 4b. The inputs used were: batch size (40 to 20 units),

material cost (10% variation), cycle times (10% variation), scrap (5% variation), breakdown (5% variation), setup times (10 to 5 minutes), and labour type (3 man floating to 4 man fixed labour). Scrap contributed 80% to the variation of profit, while the raw material costs contributed 12%. Scrap is the largest factor because every batch on each machine experiences the scrap rate from a low value of 5% to a high value of 10%. All other factors contributed less than 3.36% each.

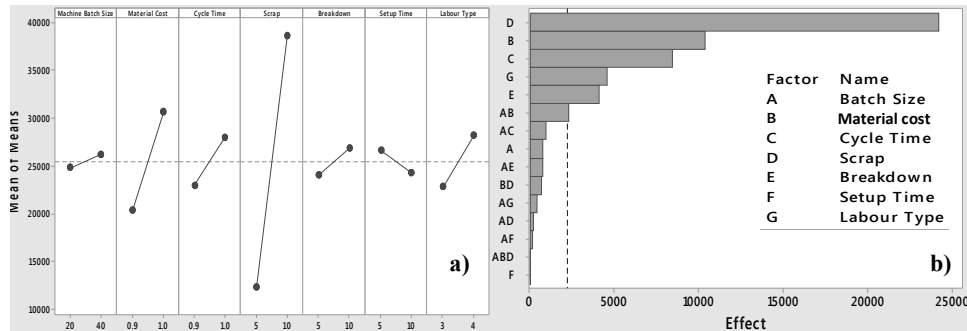


Figure 4. Pareto chart and main effects plots (response is Profit, $\alpha = 0.05$).

A study was then undertaken to consider both financial and production inputs together. In this case the raw materials, purchased part and batch size for all machines were analysed. A unit cost variation (£1) was considered for all the financial inputs and a batch variation of 20 units was considered for the production inputs. Material 2 was selected as the screening factor as it is associated with the bottleneck of the system. The analysis ranked Material 2 to have the greatest contribution (44%), followed by Material 1 and Purchased Part. The chart, Figure 5b, indicated all individual factors in the test were significant apart from Machine C Batch size. Machine C has the lowest setup time of all machines therefore it can process batches quicker; therefore it is less affected by batch size. The interactions between Material 1 and the purchased part, and Material 2 and the purchased part were significant. Moreover both these interactions were between factors associated with P production. The results also illustrate limited variable interactions and the greater significance of the price of materials and parts over the studied production variations.

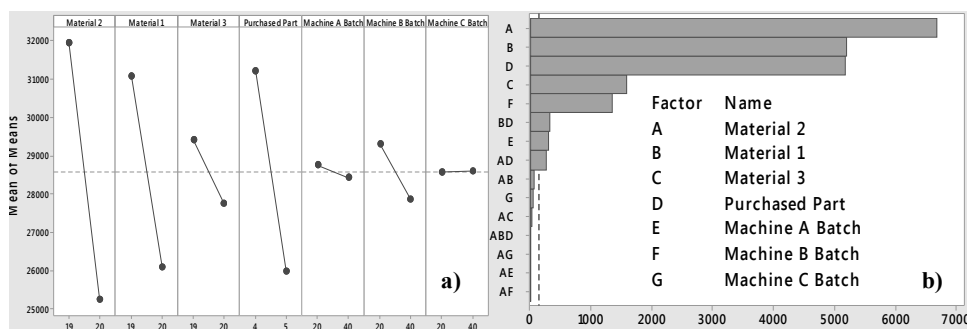


Figure 5. Pareto chart and main effects plots (response is Profit, $\alpha = 0.05$).

Based on the preceding results further parametric simulations of Batch Size and Setup Time were undertaken, Figure 5. In general the predictions indicate increasing Setup Time reduced Profit but surprisingly greater Batch Size increased Profit. These results indicate the examine Batch Size range is below the optimum for the system. Further analysis determined the optimum batch size (based on profit) was dependent on setup time but in all cases was outside the examined range (Setup Time of 10 minutes – 50 to 60 Batch Size is optimal, Setup Time of 40 minutes – 90 to 100 Batch Size is optimal).

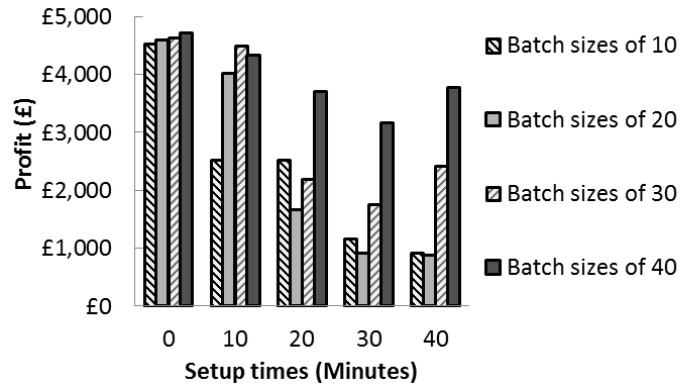


Figure 5. Predicted Profit with varying Batch Size and Setup Time.

Finally comparing the Profit trends between the 28 and 60 week simulations, the extended simulations appear to smooth volatility caused by the nature of the P's and Q's demanded, Figure 2. The extended period resulted in larger profit values and this smooths the impact of any variations due to sale transactions in the final week. However in both sets of results there is clear evidence that the work in the system (either complete or incomplete) at the end of the reporting period can influence the predicted profit. For example Figure 6 illustrates a simple case examining variations in Setup Time. In this case decreasing Setup Time from 10 to 0 minutes has no impact on the predicted profit. However it clearly results in parts making it to the FGS but not being shipped in the period. To address this weakness it is possible to represent the value of complete or incomplete work in the manufacturing system using a Weighted Asset Value (WAV) calculation, Equation 4 to 6. Figure 6 illustrates how the addition of a WAV for the units in the FGS may better represent the effectiveness of the manufacturing system in the period.

$$\text{Conversion period (days)} = \frac{\text{Inventory}}{\text{COGS}} \times \text{Number of working days} \quad (4)$$

$$\text{Completion ratio} = \frac{\text{Inventory conversion period} - \text{Asset conversion period}}{\text{Inventory conversion period}} \quad (5)$$

$$\text{WAV}_{(FGS)} = \text{Asset}_{(FGS)} \times \text{Expected Profit} \times \text{Completion ratio}_{(FGS)} \quad (6)$$

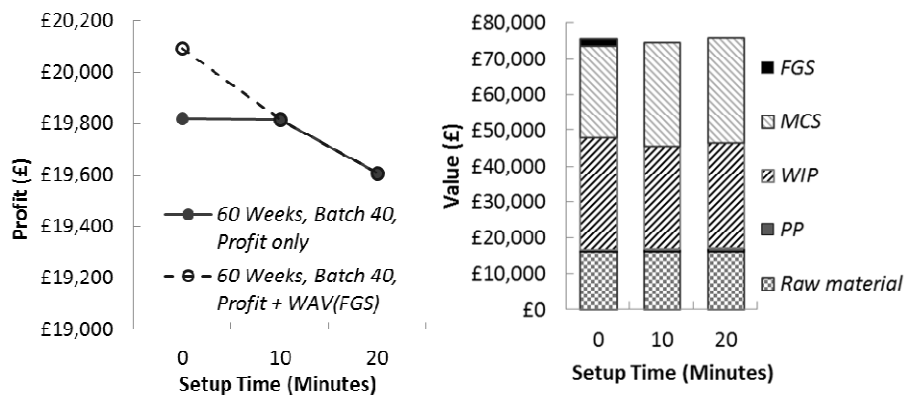


Figure 6. Predicted Profit and end of period Weighted Asset Values with varying Setup Times.

5. CONCLUSIONS

The documented research demonstrates an integrated simulation methodology which combines engineering and financial metrics. The paper demonstrates a DOE approach can identify the critical variables and potential variable interactions. The simulation results also demonstrate the challenge of coupling engineering and financial metrics considering a system with variability and the challenge of reducing a simulation output for a set period to a single value. The results illustrate the need to carefully consider financial metrics, and the risk of reducing a system to a single financial metric.

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